The Thesis Committee for Yong Whi Song
Certifies that this is the approved version of the following thesis:

User Acceptance of an Artificial Intelligence (AI) Virtual Assistant: An Extension of the Technology Acceptance Model

APPROVED BY
SUPERVISING COMMITTEE:

Matthew S. Eastin, Supervisor

Gary B. Wilcox

User Acceptance of an Artificial Intelligence (AI) Virtual Assistant: An Extension of the Technology Acceptance Model

by

Yong Whi Song

Thesis

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Master of Arts

The University of Texas at Austin

May 2019

Dedication

I dedicate my thesis to my family for their love and support.

Acknowledgements

I would like to express my appreciation to Dr. Matthew Eastin and Dr. Gary Wilcox for their guidance and support on this thesis.

Abstract

User Acceptance of an Artificial Intelligence (AI) Virtual Assistant: An Extension of the Technology Acceptance Model

Yong Whi Song, M.A.

The University of Texas at Austin, 2019

Supervisor: Matthew S. Eastin

This study investigates the factors affecting the intention to adopt and use an artificial intelligence (AI) virtual assistant. This study examines and extends the technology acceptance model (TAM). Study results support the TAM, wherein perceived usefulness and perceived ease of use have a positive impact on behavioral intention to use an AI virtual assistant. Moreover, perceived ease of use and subjective norm have a positive effect on perceived usefulness. This study discusses both theoretical and practical implications of the findings.

Keywords: Artificial Intelligence (AI), AI Virtual Assistant, Technology Acceptance Model (TAM)

Table of Contents

List of Tables

List of Figures

Chapter I: Introduction

An AI virtual assistant is software that understands voice commands of a user and executes comparable tasks. Current AI virtual assistants provide a wide variety of services—from reporting weather information to purchasing products—and the capabilities of AI virtual assistants are expanding day by day. Amazon Alexa, Google Assistant, and Apple's Siri are leading AI virtual assistants on the current market, and their software is integrated into various smart devices, such as smartphones, smart speakers, smart wearable devices, and smart TVs (Dousay & Hall, 2018). The AI virtual assistant market continues to grow; it is expected that 55% of U.S. households will own a smart speaker by 2022, and 8 billion AI virtual assistants are forecast to be used by 2023 (Johnson, 2018; Juniper Research, 2018). The overall worldwide AI market is expected to be $105 billion in 2025 (Tractica, 2018).

Although an AI virtual assistant is "the next big thing," along with its prospects for market growth, current theoretical understanding of individuals' acceptance of an AI virtual assistant is deficient. Therefore, the goals of this study are to scrutinize (1) which factors influence individuals to choose to use an AI virtual assistant, and (2) how individuals come to accept and use an AI virtual assistant. This study examines the technology acceptance model (TAM) by applying two key variables: perceived usefulness and perceived ease of use. Furthermore, current study extends the TAM by integrating two critical psychological factors of the theory of reasoned action (TRA)—subjective norm and attitude—and develops a new research model that predicts individuals' behavior intentions to use an AI virtual assistant.

This paper is structured as follows. Chapter II reviews the literature relating to an AI virtual assistant technology, the TAM, and TRA. Chapter III discusses the data collection methods and procedures. Chapter IV reports the results of the statistical analysis. Chapter V concludes this paper with a discussion of both theoretical and practical implications of the study findings.

Chapter II: Literature Review

ARTIFICIAL INTELLIGENCE (AI) VIRTUAL ASSISTANT

An artificial intelligence (AI) virtual assistant is software that can understand a user's natural language voice commands and perform corresponding tasks or provide comparable services for the user. An AI virtual assistant is different from previous text-based virtual assistant software (i.e., chatbots) as it is driven by AI algorithm functions such as automatic speech recognition (ASR) as well as natural language understanding (NLU) technology ("Amazon Alexa," n.d.). ASR is a "technology that converts spoken words into text," whereas NLU is a technology that is an "artificial intelligence centered on recognizing patterns and meaning within human language" ("Amazon Alexa," n.d.). Currently, Apple's Siri, Amazon's Alexa, Google's Google Assistant, Microsoft's Cortana, and Samsung's Bixby are leading AI virtual assistants on the market. These AI virtual assistants are integrated into various smart devices such as smartphones, smart speakers, smart wearable devices, smart TVs, smart cars and other similar devices that can respond to natural language voice commands and execute tasks or requests (Dousay & Hall, 2018). Table 1 compares various AI virtual assistants of Apple, Amazon, and Google.

	Apple's Siri	Amazon's Alexa	Google's Google Assistant
Launched Year	2011	2014	2016
Popular Compatible Devices	HomePod iPhones	Echo Dot Echo Echo Plus Echo Show Echo Spot Android and iPhones through Alexa app	Google Home Mini Google Home Google Home Max Android and iPhones through Google Assistant app
Number of Compatible Brands	50	3,500	500
Supported Languages	Arabic; Chinese; Danish; Dutch; English (AU, CA, IN, NZ, SG, US, ZA); Finnish; French; German; Hebrew; Italian; Japanese; Korean; Malay; Norwegian; Portuguese; Russian; Spanish; Swedish; Thai; Turkish.	English (AU, CA, GB, IN, US); German; Japanese.	English (AU, CA, GB, US); French; German; Japanese

Note. Reprinted from *The best voice assistants* by Meg Cannistra, retrieved from https://www.reviews.com/voice-assistant/ Copyright 2019 by Reviews.com

Table 1: AI Virtual Assistants Comparison

The basic operating principles of an AI virtual assistant are as follows. First, a user wakes up an AI virtual assistant software by verbalizing a certain "wake-word" (e.g., "Hey, Siri," "Alexa," or "Hey, Google"), then, the software automatically starts recording the user's voice command and sends it to a specialized Internet server, which interprets and processes the voice message. Lastly, the server will supply appropriate information to the AI virtual assistant to complete the requested tasks, and the assistant will respond to the user based on text-to-speech (TTS) technology (Hoy, 2018; Yang & Lee, 2018).

According to Hoy (2018), current AI virtual assistants can do the following representative tasks: (a) make phone calls and send and read text messages and emails; (b) set timers and reminders, organize calendar schedules, and make lists; (c) answer basic informational questions (e.g., reporting weather information); (d) play media, such as music and video files, requested by the user; (e) chat and tell jokes and stories; (f) control Internet-of-Things (IoT) devices such as locks, lights, home security cameras, and thermostats; and (g) provide online shopping. The range of work that an AI virtual assistant can do is expanding day by day. For instance, Amazon's Alexa Skills Kit (ASK) lets developers create various voice-driven capabilities (i.e., Alexa Skills) using a collection of self-service application program interfaces (APIs; "Alexa Skills Kit", n.d.). As a result, Amazon's Alexa Skills counts surpass 80,000 worldwide (Day, 2019).

Previous virtual assistant research has broadly focused on various topics such as establishing users' privacy concerns (Easwara Moorthy & Vu, 2015) and the suitability of software for certain user groups, including the elderly (Reis, Paulino, Paredes, & Barroso, 2017) and patients with mild traumatic brain injury (mTBI) and posttraumatic stress disorder (PTSD; Wallace & Morris, 2018). However, a theoretical understanding of why users adopt AI virtual assistants is still in its infancy, and despite the rapid technological growth, there is a dearth of research investigating AI adoption. Most recently, Yang and Lee (2018) found that both the perceived usefulness and perceived enjoyment have significant effects on usage intentions. While Yang and Lee (2018) applied the perceived usefulness construct from the technology acceptance model (TAM), they did not investigate other functions of the TAM or other theories of adoption such as the theory of reasoned action (TRA).

TECHNOLOGY ACCEPTANCE MODEL (TAM)

The TAM, originally introduced by Davis (1989) as an extension of the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), is a theoretical model explaining individuals' intentions to adopt or reject a new technology. The TAM has proven to be a prominent framework in understanding factors affecting the acceptance of new technology (Marangunić & Granić, 2015). When comparing the TPB and TRA, the TRA is based on general human behavior and acceptance intention along with individuals' subjective norms and attitudes, whereas the TAM focuses specifically on technology contexts and user acceptance (Davis et al., 1989).

The TAM provides two key factors that users take in accepting technology—perceived usefulness and perceived ease of use—as well as attitudes toward technology use, behavioral intention, and technology adoption (Davis et al., 1989). In a field study, Davis (1989) demonstrated that individuals' behavioral intent to use an electronic mail system (known as Profs) and a file editor (known as XEDIT) resulted from both their perceived usefulness and perceived ease of use (Davis, 1989; Rauniar, Rawski, Yang, & Johnson, 2014). Perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his or her performance" (Davis, 1989, p. 320). High perceived usefulness among users would lead to the continuance of their positive use–performance relationships (Davis, 1989). Perceived ease of use is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). Here, users are more likely to feel favorable toward technology and accept a technology that is perceived to be easier to use than another (Davis, 1989). As Figure 1 depicts, the TAM is a path model stating that technology adoption is determined by an individual's behavioral intention, which jointly depends on the individual's attitudes toward adopting the technology and its perceived usefulness (Davis et al., 1989; N. Park, 2010).

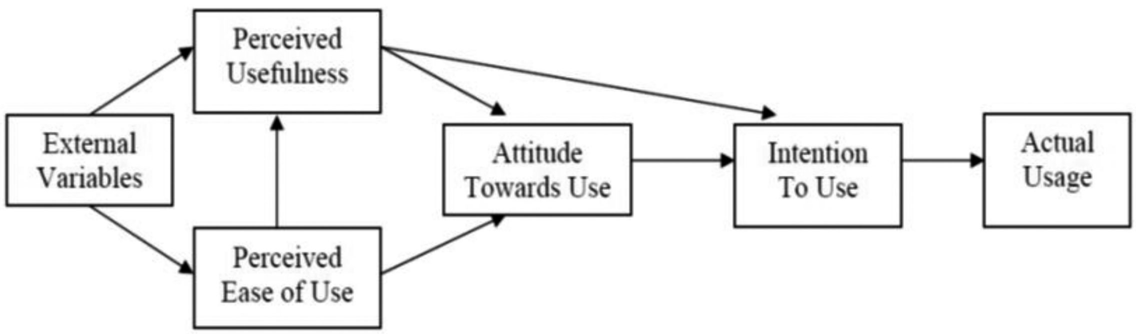


Figure 1: The Technology Acceptance Model (Davis, 1989).

Many prior studies have applied the TAM to the contexts of various technologies (N. Park, 2010). These studies have extended and test the theory's effectiveness. As stated by N. Park (2010), in the early days after the theory was published, the majority of research was about applying the TAM to personal computer use and relatively easy software operations, such as operating systems (Karahanna, Straub, & Chervany, 1999), word processing and spreadsheet software packages (Chau, 1996; Davis et al., 1989; Doll, Hendrickson, & Deng, 1998; Mathieson, 1991), and electronic mail (Davis, 1989; Karahanna & Straub, 1999). In the 2000s, the trend in TAM studies was to validate the application of the TAM to Internet and Internet-based technologies (N. Park, 2010;

Marangunić & Granić, 2015). For instance, several studies on the TAM were conducted in the contexts of e-learning (Cheung & Vogel, 2013; Farahat, 2012; Gong, Xu, & Yu, 2004; N. Park, Lee, & Cheong, 2007; Zhang, Zhao, & Tan, 2008), Internet banking (Chan & Lu, 2004; Nasri & Charfeddine, 2012), digital library system (Davies, 1997; Hong, Thong, Wong, & Tam, 2002), online auctions (Stern, Royne, Stafford, & Bienstock, 2008), telemedicine (Chau & Hu, 2002; Hu, Chau, Sheng, & Tam, 1999) and healthcare information systems (Pai & Huang, 2011). Recently, with the advent of smartphones and social media, scholars have researched the relevance of the TAM to "smart" technology adoption such as social media (Cha, 2010; Rauniar et al., 2014), smartphones (Joo & Sang, 2013), tablet computers (Ducey & Coovert, 2016), wearable devices (Lunney, Cunningham & Eastin, 2016), mobile cloud services (E. Park & Kim, 2014), and mobile payment systems (Ooi & Tan, 2016; Ramos-de-Luna, Montoro-Ríos, & Liébana-Cabanillas, 2016).

Perceived Usefulness

In the current study, perceived usefulness is defined as the degree to which the user believes that using an AI virtual assistant will enhance his or her performance (Davis, 1989). Generally, perceived usefulness is regarded as being a more direct and stronger factor on the intention to adopt technology than perceived ease of use (Cha, 2010). Davis, et al. (1989) found that perceived usefulness is a major determinant of an individual's intention to adopt new technology, whereas perceived ease of use is a secondary determinant. Multiple studies discovered positive effects on perceived usefulness, attitudes, and behavioral intention toward technology adoption. According to Gong et al. (2004), users' perceived usefulness has positive effects on attitude and behavioral intention of users in accepting Web-based learning systems. Bhattacherjee and Hikmet

(2008) showed that users' perceived usefulness of information technology positively influenced their intentions to use the technology. Additionally, Pai and Huang (2011) found perceived usefulness to be positively related to a user's intention to adopt a healthcare information system. Similarly, Rauniar et al. (2014) revealed that individuals' perceived usefulness of social media (i.e., Facebook) is positively related to their intention to use social media. Lunney et al. (2016) also argued that perceived usefulness positively influenced users' attitudes toward and adoption of wearable fitness devices. Consequently, this current study hypothesizes that individuals' perceived ease of use of an AI virtual assistant will not only result in positive attitudes toward the technology but also positively influence behavioral intentions to adopt the technology. Therefore, this study sets forth the following hypotheses:

H1a: Perceived usefulness will have a positive effect on attitude toward an AI virtual assistant.

H1b: Perceived usefulness will have a positive effect on behavioral intention to use an AI virtual assistant.

PERCEIVED EASE OF USE

Within the current study, perceived ease of use is defined as the degree to which a user believes that using an AI virtual assistant would be free of effort (Davis, 1989). The original TAM indicated that perceived ease of use functions through perceived usefulness and has an indirect effect on behavioral intention to use (see Figure 1). Several studies, however, have found that perceived ease of use is the primary factor positively influencing not only perceived usefulness but also the users' attitudes and behavioral intentions toward technologies ay. Farahat (2012) found that perceived ease of use is a significant determinant of (a) perceived usefulness, (b) individuals' attitudes, and (c) behavioral intentions toward online learning technology. Joo and Sang (2013) also found that perceived ease of Apple's iPhone had positive effects on both perceived usefulness and behavioral intention toward their iPhone usage. Similarly, Lunney et al. (2016) found that perceived ease of use positively influenced individuals' attitudes toward wearable fitness devices. Based on previous findings, the current study assumes that an AI virtual assistant's perceived ease of use will not only result in positive attitudes toward the technology but also positively influence behavioral intentions to adopt the technology. Therefore, the following hypotheses are proposed:

H2a: Perceived ease of use will have a positive effect on perceived usefulness.

H2b: Perceived ease of use will have a positive effect on attitude toward an AI virtual assistant.

H2c: Perceived ease of use will have a positive effect on behavioral intention to use an AI virtual assistant.

SUBJECTIVE NORM

In 1975, Fishbein and Ajzen proposed the TRA, arguing that human beings are quite rational, in that they systematically take into account the meaning of their actions before engaging in a given action (see Figure 2). Specifically, individuals will intend to behave in a certain way when they think other people who are important to them should do it (i.e., subjective norm) and when they assess it positively (i.e., attitude toward the behavior; Fishbein & Ajzen, 1975; Ajzen & Fishbein, 1980). TAM studies have often incorporated the TPB to scrutinize the relationships between subjective norm, attitude, and behavioral intention to use (Lunney et al., 2016). For instance, even though Davis's (1989) original TAM did not include subjective norm, TAM2, the extended model of TAM proposed by Venkatesh and Davis (2000), and TAM3 by Venkatesh and Bala

(2008), incorporated subjective norm and found that subjective norm positively influences both behavioral intention and perceived usefulness (see Figure 3 and Figure 4).

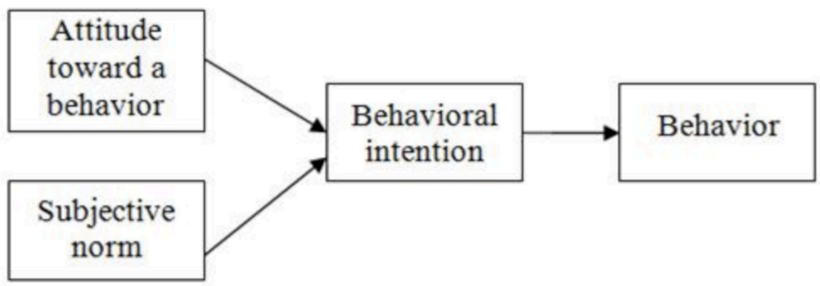


Figure 2: The Theory of Reasoned Action (Fishbein & Ajzen, 1975).

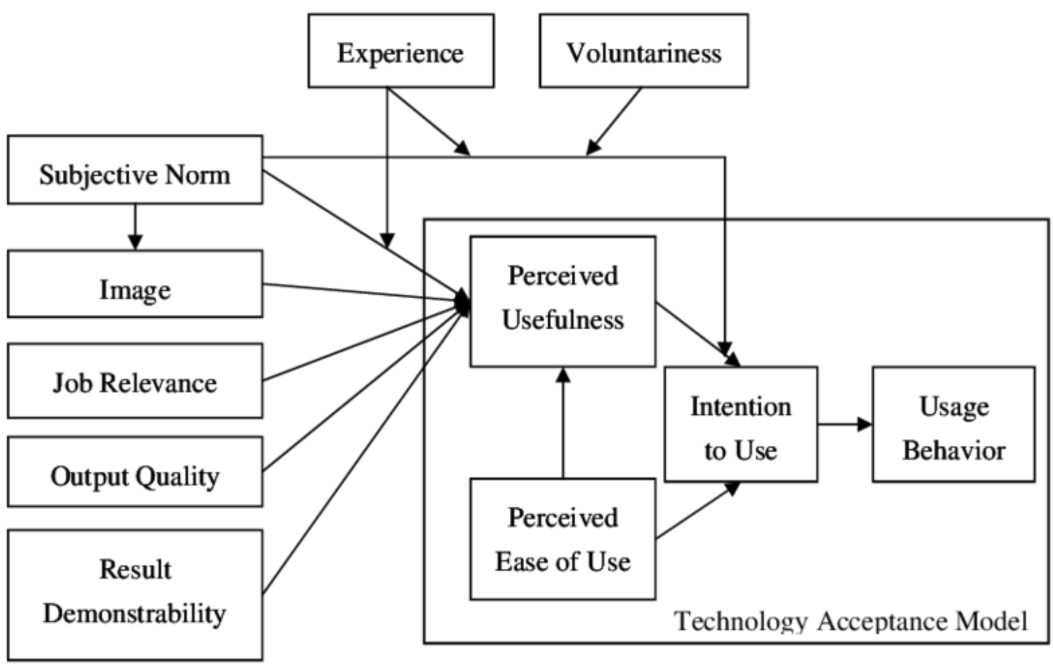


Figure 3: The Extended Technology Acceptance Model (TAM2; Venkatesh & Davis, 2000).

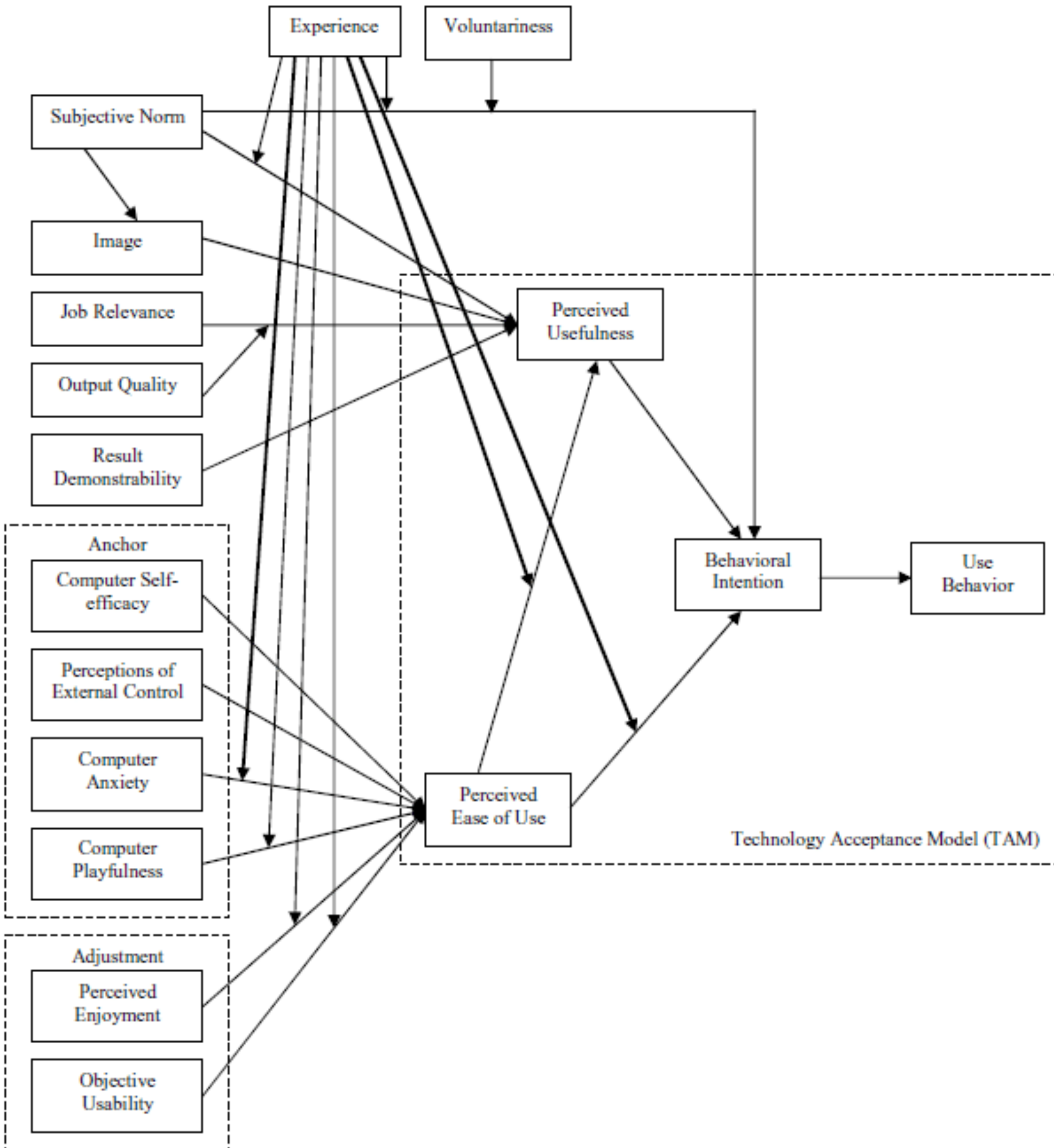


Figure 4: The Extended Technology Acceptance Model (TAM3; Venkatesh & Bala, 2008).

Subjective norms, a function of normative beliefs, is defined as one's perceived social pressures that are placed on a person regarding whether or not to perform a behavior (Ajzen & Fishbein, 1980). Simply, when an individual must decide whether to perform a behavior or not, an inspiring person in the surrounding environment will influence the individual's behavior believes through perceived social pressure to perform the behavior (Fishbein & Ajzen, 1975; Ajzen & Fishbein, 1980). and user acceptance (Davis et al., 1989).

For the current study, subjective norm is described as one's perceived social pressure to adopt or not to adopt the use of an AI virtual assistant (Ajzen & Fishbein, 1980). Subjective norm is related to behavioral intention because individuals may decide to perform a behavior if important referent people for them expect them to perform the behavior, even if they do not feel positive about that behavior (Venkatesh & Davis, 2000). The direct impacts of subjective norm on both perceived usefulness and behavioral intention toward technology adoption have proven to be significant in various TAM-related studies. That is, Schepers and Wetzels's (2007) meta-analytic study found a significant influence of subjective norm on both perceived usefulness and behavioral intention to use. Further, Cheung and Vogel (2013) found that users' subjective norm, especially as represented by peers, positively influenced behavioral intentions toward online learning technology. Most recently, Lunney and colleagues (2016) found that perceived subjective norm is significantly related to the use of wearable fitness devices. This aligns with studies suggesting subjective norm has a significant effect on behavioral intentions toward mobile payment technology use (i.e., near-field communication [NFC]; Ramos-de-Luna et al., 2016). In accordance with these findings, the following assumption is made:

H3a: Subjective norm will have a positive effect on perceived usefulness.

H3b: Subjective norm will have a positive effect on behavioral intention to use an AI virtual assistant.

ATTITUDE TOWARD TECHNOLOGY USE

According to the TRA, attitude toward the behavior is defined as "the person's judgment that performing the behavior is good or bad, that he/she is in favor of or against performing the behavior" (Ajzen & Fishbein, 1980, p. 6). People who believe that performing a behavior will mostly have positive consequences will have a favorable attitude toward carrying out the action, while those who believe that carrying out the action will mostly have negative consequences will maintain unfavorable attitudes (Ajzen & Fishbein, 1980). As a crucial component of the TAM (Davis, 1989), attitude is a determinant of behavioral intention toward technology use, which in turn predicts the adoption (Lunney et al., 2016). In other words, attitude is an important antecedent of behavioral intention toward technology use (Ajzen & Fishbein, 1980; Ramos-de-Luna et al., 2016).

Many researchers have found that a positive attitude toward technology use is a significant factor of behavioral intention and technology adoption. For instance, individuals' attitude toward online learning technology is a significant determinant of their intention to use the technology (Cheung & Vogel, 2013; Farahat, 2012). Suki and Suki (2011) also supported that attitude has a positive effect on behavioral intention toward using 3G mobile services. Similarly, E. Park and Kim (2014) argued that user attitudes toward a mobile cloud service had a positive effect on the intention to use the service.

In this study, attitude toward technology use is defined as a person's favorable or unfavorable evaluation of using an AI virtual assistant (Ajzen & Fishbein, 1980).

Individuals’ attitudes toward technology use are assumed to have a positive impact on their behavioral intentions because a more positive attitude toward technology use will result in stronger intent to use the technology (Fishbein & Ajzen, 1975; Davis, 1989). Based on these findings, this study posits the following hypothesis:

H4: Attitude toward an AI virtual assistant will have a positive effect on behavioral intention to use that AI virtual assistant.

The proposed research model of this study is illustrated in figure 5.

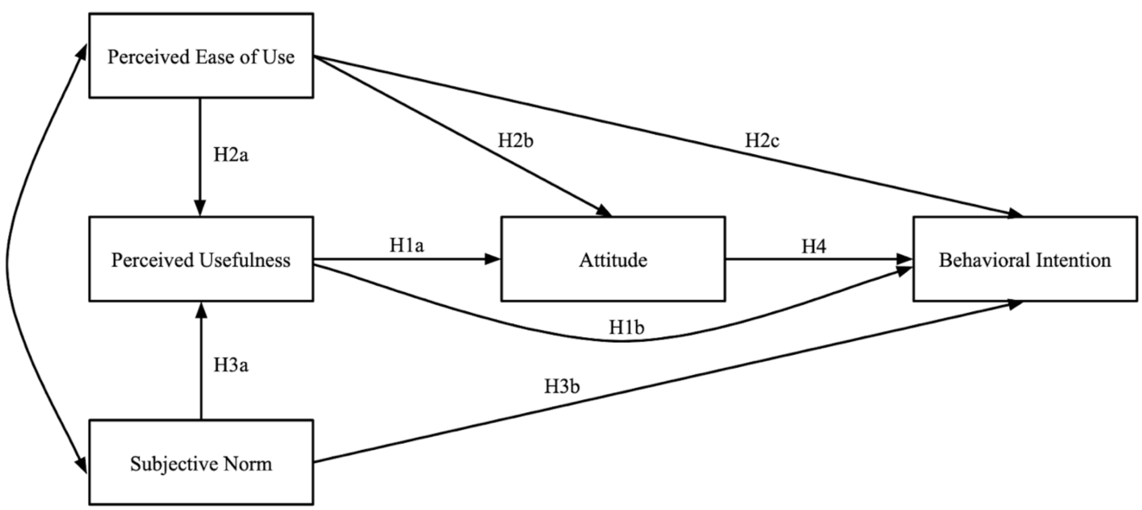


Figure 5: Hypothesized Research Model

Chapter III: Methodology

Sample

Study participants were recruited through Amazon's Mechanical Turk (MTurk). To be eligible for this study, participants were required to be in the United States and be at least 18 years old. All participants were informed that their participation in the study was entirely voluntary, and they each received 50 cents upon completion of the online survey. A total of 450 responses were received, of which 433 were finally accepted as the final sample after excluding those with missing or erroneous data.

Participants (N = 433) consisted of 50% males and ages ranged from 21 to 70 (M = 39.71, SD = 11.96). The majority of respondents were White (76%), followed by African American (9%), Asian (7%), Hispanic or Latino (4%), and Other/Biracial (4%). Education levels included those with bachelor's degrees (41%), followed by some college credit without degrees (23%), associate's degrees (12%), master's degrees (12%), high school diplomas or GEDs (8%), professional degrees (1%), and doctorate degrees (1%). Of the participants, most earned a yearly salary of $40,000–$59,999 (23%) or $20,000–$39,999 (23%), followed by those earning between $60,000–$79,999 (22%), more than $100,000 (14%), less than $20,000 (10%), and $80,000–$79,999 (8%). The majority of participants reported they are currently employed, including both full-time (79%) and part-time (13%).

Measures

The online survey questionnaire consisted of five major sections that assess (a) perceived usefulness, (b) perceived ease of use, (c) subjective norm, (d) attitude toward an AI virtual assistant, and (e) behavioral intention to use an AI virtual assistant.

Questionnaires were based on several previous well-established measurement scales and modified to suit an AI virtual assistant technology context.

Perceived Usefulness

Perceived usefulness was measured using five items adapted from Davis's (1989) TAM scale. Items including "Using an AI virtual assistant for accomplishing tasks increases my productivity", "Using an AI virtual assistant improves my performance at accomplishing tasks", "Using an AI virtual assistant enhances my effectiveness at accomplishing tasks", "Using an AI virtual assistant enables me to accomplish tasks more quickly", and "I find an AI virtual assistant useful for me to accomplish tasks" were measured based on a 7-point Likert scale ranging from *strongly disagree* (score = 1) to *strongly agree* (score = 7) (M = 5.04, SD = 1.27, α = .95).

Perceived Ease of Use

Likewise, perceived ease of use was measured using six items adapted from Davis (1989)'s TAM scale. Items including "Learning to use an AI virtual assistant is easy for me", "I find it easy to get an AI virtual assistant to do what I want it to do", "My interaction with an AI virtual assistant is clear", "My interaction with an AI virtual assistant is understandable", "It is easy for me to become skillful at using an AI virtual assistant", and "I find an AI virtual assistant to be easy to use" were measured based on a 7-point Likert scale ranging from *strongly disagree* (score = 1) to *strongly agree* (score = 7) (M = 5.64, SD = 1.04, α = .94).

Subjective Norm

Based on scales developed by Taylor and Todd (1995) and Venkatesh and Davis (2000), subjective norm was measured using four items, a 7-point Likert scale ranging from *strongly disagree* (score = 1) to *strongly agree* (score = 7). Items to include "Generally speaking, I take the advice from people who are important to me", "Generally speaking, I like to go along with my group of friends", "People who are important to me think that I should use an AI virtual assistant", and "People who influence my behavior think that I should use an AI virtual assistant" (M = 4.73, SD = .96, α = .76).

Attitude Toward an AI Virtual Assistant

Four items for measuring an individual's attitude toward an AI virtual assistant were derived from Cheng, Lam, and Yeung (2006) and S. Y. Park (2009). Items including, "I feel positive toward an AI virtual assistant", "I feel that using an AI virtual assistant is pleasant", "Using an AI virtual assistant is a good idea", and "Using an AI virtual assistant is a smart way to get things done" were measured on a 7-point Likert scale, anchored with *strongly disagree* (score = 1) to *strongly agree* (score = 7) (M = 5.39, SD = 1.27, α = .95).

Behavioral Intention to Use an AI Virtual Assistant

Behavioral intention was measured by utilizing Venkatesh and Davis's (2000) TAM2 scale. Three questionnaires with 7-point Likert scales, ranging from *strongly disagree* to *strongly agree*, were used to measure behavioral intention. Participants were asked about items: "I intend to use an AI virtual assistant", "I predict that I would use an AI virtual assistant", and "Using an AI virtual assistant is something I would do" (M = 5.60, SD = 1.37, α = .95).

DATA ANALYSIS

This study employed a structural equation modeling (SEM) approach. Every hypothesized relationship was tested through the predicted model using IBM AMOS 25 with the default maximum likelihood estimation method. To judge the overall model fit, the study used the following four model fit indices: (a) Chi-square, (b) root mean square error of approximation (RMSEA), (c) goodness of fit index (GFI), and (d) comparative fit index (CFI). As indicated in Table 2, the research model fits the data well.

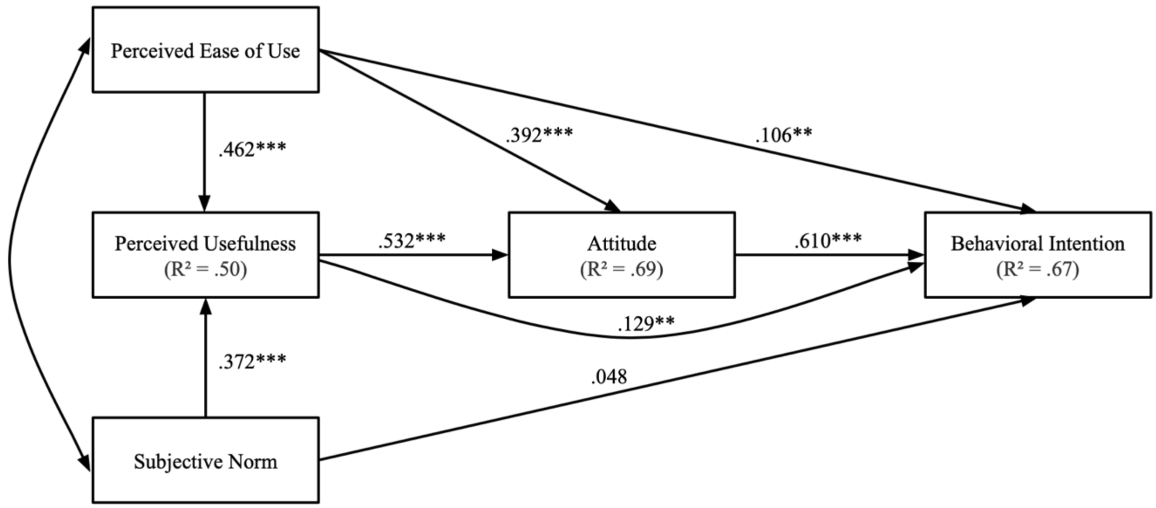
Fit Indices	Values	Recommended Guidelines
χ^2	3.141, $p = .076$	$p > 0.05$
RMSEA	.070	< 0.08
GFI	.997	≥ 0.95
CFI	.998	≥ 0.95

Note. Recommended guidelines based on Hooper, Coughlan, and Mullen (2008).

Table 2: Fit Indices for the Research Model

Chapter IV: Results

As summarized in Figure 6 and Table 3, the results supported all hypotheses in the research model, with the exception of H3b. Perceived usefulness had significant positive effects on attitude toward an AI virtual assistant (H1a, $\beta = .532$, $p < .001$) and behavioral intention to use an AI virtual assistant (H1b, $\beta = .129$, $p < .01$). Moreover, perceived ease of use had significant positive effects on perceived usefulness (H2a, $\beta = .462$, $p < .001$), attitude toward an AI virtual assistant (H2b, $\beta = .392$, $p < .001$), and behavioral intention to use an AI virtual assistant (H2c, $\beta = .106$, $p < .01$). While subjective norm was significantly positively related to perceived usefulness (H3a, $\beta = .372$, $p < .001$), it was not related to behavioral intention to use an AI virtual assistant (H3b, $\beta = .048$, $p > .05$). Attitude toward an AI virtual assistant has a significant positive effect on behavioral intention to use an AI virtual assistant (H4, $\beta = .610$, $p < .001$). Lastly, 67% of the variance in behavioral intention, 69% of the variance in attitude, and 50% of the variance in perceived usefulness were explained from the model.



Note. ** $p < .01$, *** $p < .001$

Figure 6: Research Model Results

Hypothesis	Relationship	Standardized coefficient	Supported
H1a	Perceived Usefulness → Attitude	.532***	Yes
H1b	Perceived Usefulness → Behavioral Intention	.129**	Yes
H2a	Perceived Ease of Use → Perceived Usefulness	.462***	Yes
H2b	Perceived Ease of Use → Attitude	.392***	Yes
H2c	Perceived Ease of Use → Behavioral Intention	.106**	Yes
H3a	Subjective Norm → Perceived Usefulness	.372***	Yes
H3b	Subjective Norm → Behavioral Intention	.048	No
H4	Attitude → Behavioral Intention	.610***	Yes

Note. ** $p < .01$, *** $p < .001$

Table 3: Summary of Hypothesis Tests

Chapter V: Discussion and Conclusions

This study pioneered efforts and contributions in applying critical variables from the TAM—perceived usefulness and perceived ease of use—and the TRA—subjective norm and attitude—to the context of an AI virtual assistant, an area of research that is still in its infancy. Moreover, by employing a structural equation modeling analysis, this study discovered how individuals come to choose to use an AI virtual assistant. The findings of the present study have both theoretical and practical implications for AI researchers, software developers, service providers, marketers, and advertisers.

The results of this study supported Davis's (1989) original TAM. The current study found that perceived usefulness has significant effects on individuals' attitude toward an AI virtual assistant and behavioral intention to adopt an AI virtual assistant. These results also support prior TAM literature that scrutinized perceived usefulness as a major factor affecting attitude and behavioral intention to use (Bhattacherjee & Hikmet, 2008; Cha, 2010; Davis, 1989; Davis, et al., 1989; Gong et al., 2004; Lunney et al., 2016; Pai and Huang, 2011; Rauniar et al., 2014). The results of this study suggest AI virtual assistant software developers and corporations should improve their software by further enhancing consumer usefulness. The results also suggest to marketers and advertisers that strategically positioning an AI virtual assistant as a useful technology and publicizing it will let their audience have positive attitudes toward the AI virtual assistant and eventually purchase the technology.

Consistent with Davis (1989), current study discovered perceived ease of use has a direct influence on perceived usefulness and individuals' attitude toward an AI virtual assistant. It is advisable for software manufacturers of AI virtual assistants, especially those in its development stage, to understand that the ease of software operation is one of the top features sought by potential consumers. Additionally, an interesting finding from this study is that perceived ease of use is a direct positive determinant of behavioral intention to use an AI virtual assistant. The original TAM by Davis (1989) did not state that perceived ease of use has a direct relationship with behavioral intention. Therefore, this study contributes to the development of the original TAM by providing an extended framework for future research.

This study employed the TRA (Fishbein & Ajzen, 1975) by using two key variables: subjective norm and attitude. Data indicated that subjective norm is directly related to perceived usefulness, which aligns with previous literature (Schepers & Wetzels, 2007). However, this study uncovered that subjective norm is not a direct determinant variable of individuals' behavioral intention to use. These results imply that influential people in individuals' surrounding environment may directly affect the way individuals contemplate how an AI virtual assistant is useful for them, but they may not directly affect the way individuals have adopt and use the new technology.

Based on the results, this study believes that subjective norm is still a consequential variable for consideration when it comes to individuals deciding whether to adopt an AI virtual assistant, and thus should not be disregarded by researchers and practitioners. There are two reasons for this. First, according to this study's structural equation model analysis, subjective norm is directly related to perceived usefulness. Further, perceived usefulness is directly related to behavioral intention as well as linked through individuals' attitudes. Thus far, there is still a relationship between subjective norm and behavioral intention to use an AI virtual assistant (i.e., Subjective Norm → Perceived Usefulness → (Attitude) → Behavioral Intention), although it is not directly connected. Second, a correlation analysis demonstrated a significant positive relationship between subjective norm and behavioral intention to use an AI virtual assistant (r = .47,

$p < 0.01$; see Table 4). Namely, as individuals' subjective norm increases, their behavioral intention also increases.

Correlations					
Perceived Usefulness	1.00				
Perceived Ease of Use	.62**	1.00			
Subjective Norm	.56**	.41**	1.00		
Attitude	.77**	.72**	.50**	1.00	
Behavioral Intention	.69**	.64**	.47**	.81**	1.00

Note. ** $p < .01$

Table 4: Correlations

Along with subjective norm, this study supports previous TRA literature suggesting attitude is directly and positively related to behavioral intention to adopt and use new technology (Cheung & Vogel, 2013; E. Park & Kim, 2014; Farahat, 2012; Suki & Suki, 2011). This finding indicates that if an individual has a positive attitude toward an AI virtual assistant, he or she is more inclined to adopt and use the technology. For marketers and advertisers planning to publicize an AI virtual assistant, appreciating that potential users' positive attitude toward the technology will be a significant factor in their technology adoptions is indispensable. In other words, it is important for marketing and advertising practitioners to allow their potential consumers to realize that the use of their AI virtual assistant software will be pleasing to use. Furthermore, software developers of AI virtual assistants are encouraged to develop their software to maximize positive attitudes and minimize negative attitudes of users.

Although the current study furnishes new insights into understanding user acceptance of an AI virtual assistant, it nonetheless has a few limitations, one of which is the characteristics of the study participants. This study recruited survey participants from Amazon's MTurk, an Internet crowdsourcing platform. One of the preeminent advantages of using MTurk as a tool for data collection in social science research is that participants are more attentive to survey instructions than college subject pool samples (Hauser & Schwarz, 2016). However, given that MTurk is an online-only survey platform, it is expected that the majority of participants of this study were more likely to be proficient in the latest technologies. Therefore, the composition of such participants might raise the mean value of general responses. Future studies can diversify data collection methods to include samples with different technology interests and aptitudes.

There may be other variables that may affect individuals' behavioral intention to adopt an AI virtual assistant. One of the prominent challenges that practitioners face in popularizing AI virtual assistants is that many people have a distrust of security and privacy concerns regarding AI technology. According to a survey by PricewaterhouseCoopers (PwC; 2018), 38% of nonusers of AI virtual assistants mentioned they refused to adopt the technology because they did not want a device monitoring their daily life, and 28% specified it was because of their unease with data security and privacy issues. Given that individuals' perceived trust, security, and privacy may affect their adoption and use of an AI virtual assistant, future studies can integrate these variables into the research model.

Appendix A: The IRB Approval Letter

OFFICE OF RESEARCH SUPPORT & COMPLIANCE

THE UNIVERSITY OF TEXAS AT AUSTIN

P.O. Box 7426, Austin, Texas 78713 · Mail Code A3200
(512) 471-8871 · FAX (512) 471-8873

FWA # 00002030

Date:
PI:
Dept:
Title:

Re: IRB Exempt Determination for Protocol Number

Dear

Recognition of Exempt status based on 45 CFR 46.101(b)(2).

This determination is for a three year period beginning on and ending on at 12 a.m. midnight. A progress report will be required prior to this end date if research is still ongoing.

Responsibilities of the Principal Investigator:

Research that is determined to be Exempt from Institutional Review Board (IRB) review is not exempt from ensuring protection of human subjects. The Principal Investigator (PI) is responsible for the following throughout the conduct of the research study:

1. Assuring that all investigators and co-principal investigators are trained in the ethical principles, relevant federal regulations, and institutional policies governing human subject research.

2. Disclosing to the subjects that the activities involve research and that participation is voluntary during the informed consent process.

3. Providing subjects with pertinent information (e.g., risks and benefits, contact information for investigators and RSC) and ensuring that human subjects will voluntarily consent to participate in the research when appropriate (e.g., surveys, interviews).

4. Assuring the subjects will be selected equitably, so that the risks and benefits of the research are justly distributed.

5. Assuring that the IRB will be immediately informed of any information or unanticipated problems that may increase the risk to the subjects and cause the category of review to be reclassified to expedited or full board review.

6. Assuring that the IRB will be immediately informed of any complaints from subjects regarding their risks and benefits.

7. Assuring that the privacy of the subjects and the confidentiality of the research data will be maintained appropriately to ensure minimal risks to subjects.

8. Reporting, by submission of an amendment request, any changes in the research study that alter the level of risk to subjects.

These criteria are specified in the PI Assurance Statement that must be signed before determination of exempt status will be granted. The PI's signature acknowledges that they understand and accept these conditions. Refer to the Office of Research Support & Compliance (RSC) website www.utexas.edu/irb for specific information on training, voluntary informed consent, privacy, and how to notify the IRB of unanticipated problems.

1. Closure: Upon completion of the research study, a Closure Report must be submitted to the RSC.

2. Unanticipated Problems: Any unanticipated problems or complaints must be reported to the IRB/RSC immediately. Further information concerning unanticipated problems can be found in the IRB Policies and Procedure Manual.

3. 3-Year Progress Report: A 3-Year Progress Report must be submitted if the study will continue beyond the three-year qualifying period.

4. Amendments: Modifications that affect the exempt category or the criteria for exempt determination must be submitted as an amendment. Investigators are strongly encouraged to contact the IRB Program Coordinator(s) to describe any changes prior to submitting an amendment. The IRB Program Coordinator(s) can help investigators determine if a formal amendment is necessary or if the modification does not require a formal amendment process.

If you have any questions contact the RSC by phone at (512) 471-8871 or via e-mail at orsc@uts.cc.utexas.edu.

Sincerely,

James Wilson, Ph.D.
Institutional Review Board Chair

Appendix B: Online Survey Questionnaires

Perceived Usefulness

Using an AI virtual assistant for accomplishing tasks increases my productivity.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Using an AI virtual assistant improves my performance at accomplishing tasks.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Using an AI virtual assistant enhances my effectiveness at accomplishing tasks.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Using an AI virtual assistant enables me to accomplish tasks more quickly.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

I find an AI virtual assistant useful for me to accomplish tasks.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Perceived Ease of Use

Learning to use an AI virtual assistant is easy for me.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

I find it easy to get an AI virtual assistant to do what I want it to do.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

My interaction with an AI virtual assistant is clear.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

My interaction with an AI virtual assistant is understandable.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

It is easy for me to become skillful at using an AI virtual assistant.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

I find an AI virtual assistant to be easy to use.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Subjective Norm

Generally speaking, I take the advice from people who are important to me.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Generally speaking, I like to go along with my group of friends.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

People who are important to me think that I should use an AI virtual assistant.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

People who influence my behavior think that I should use an AI virtual assistant.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Attitude Toward an AI Virtual Assistant

I feel positive toward an AI virtual assistant.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

I feel that using an AI virtual assistant is pleasant.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Using an AI virtual assistant is a good idea.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Using an AI virtual assistant is a smart way to get things done.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Behavioral Intention to Use an AI Virtual Assistant

I intend to use an AI virtual assistant.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

I predict that I would use an AI virtual assistant.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

Using an AI virtual assistant is something I would do.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

References

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behaviour*. Englewood Cliffs, NJ Prentice Hall.

Alexa Skills Kit. (n.d.). Retrieved from https://developer.amazon.com/alexa-skills-kit

Amazon Alexa – What is Automatic Speech Recognition (ASR)? (n.d.). Retrieved from https://developer.amazon.com/alexa-skills-kit/asr

Amazon Alexa – What is Natural Language Understanding (NLU)? (n.d.). Retrieved from https://developer.amazon.com/alexa-skills-kit/nlu

Bhattacherjee, A., & Hikmet, N. (2008). Reconceptualizing organizational support and its effect on information technology usage: Evidence from the health care sector. *Journal of Computer Information Systems*, *48*(4), 69-76.

Cannistra. (2018, October 12). The best voice assistants. *Reviews.com*. Retrieved from https://www.reviews.com/voice-assistant/

Cha, J. (2010). Factors affecting the frequency and amount of social networking site use: Motivations, perceptions, and privacy concerns. *First Monday*, *15*(12).

Chan, S. C., & Lu, M. T. (2004). Understanding internet banking adoption and use behavior: A Hong Kong perspective. *Journal of Global Information Management (JGIM)*, *12*(3), 21-43.

Chau, P. Y. (1996). An empirical assessment of a modified technology acceptance model. *Journal of management information systems*, *13*(2), 185-204.

Chau, P. Y., & Hu, P. J. (2002). Examining a model of information technology acceptance by individual professionals: An exploratory study. *Journal of management information systems*, *18*(4), 191-229.

Cheng, T. E., Lam, D. Y., & Yeung, A. C. (2006). Adoption of internet banking: an empirical study in Hong Kong. *Decision support systems*, *42*(3), 1558-1572.

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & education*, *63*, 160-175.

Davies, C. (1997). Organizational influences on the university electronic library. *Information Processing & Management*, *33*(3), 377-392.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management science*, *35*(8), 982-1003.

Day. M. (2019, March 12). Amazon’s Alexa has 80,000 apps—and no runaway hit. *Bloomberg Businessweek.* Retrieved from https://www.bloomberg.com/news/articles/2019-03-11/amazon-s-alexa-has-80-000-apps-and-no-runaway-hit

Doll, W. J., Hendrickson, A., & Deng, X. (1998). Using Davis's perceived usefulness and ease-of-use instruments for decision making: a confirmatory and multigroup invariance analysis. *Decision Sciences*, *29*(4), 839-869.

Dousay, T. A., & Hall, C. (2018, June). Alexa, tell me about using a virtual assistant in the classroom. In *EdMedia+ Innovate Learning* (pp. 1413-1419). Association for the Advancement of Computing in Education (AACE).

Ducey, A. J., & Coovert, M. D. (2016). Predicting tablet computer use: An extended Technology Acceptance Model for physicians. *Health Policy and Technology*, *5*(3), 268-284.

Easwara Moorthy, A., & Vu, K. P. L. (2015). Privacy concerns for use of voice activated personal assistant in the public space. *International Journal of Human-Computer Interaction*, *31*(4), 307-335.

Farahat, T. (2012). Applying the technology acceptance model to online learning in the Egyptian universities. *Procedia-Social and Behavioral Sciences*, *64*, 95-104.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Reading, Mass.: Addison-Wesley.

Gong, M., Xu, Y., & Yu, Y. (2004). An enhanced technology acceptance model for web-based learning. *Journal of Information Systems Education*, *15*(4).

Hauser, D. J., & Schwarz, N. (2016). Attentive Turkers: MTurk participants perform better on online attention checks than do subject pool participants. *Behavior research methods*, *48*(1), 400-407.

Hong, W., Thong, J. Y., Wong, W. M., & Tam, K. Y. (2002). Determinants of user acceptance of digital libraries: an empirical examination of individual differences and system characteristics. *Journal of Management Information Systems*, *18*(3), 97-124.

Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modelling: Guidelines for determining model fit. *Articles*, 2.

Hoy, M. B. (2018). Alexa, Siri, Cortana, and more: An introduction to voice assistants. *Medical reference services quarterly*, *37*(1), 81-88.

Hu, P. J., Chau, P. Y., Sheng, O. R. L., & Tam, K. Y. (1999). Examining the technology acceptance model using physician acceptance of telemedicine technology. *Journal of management information systems*, *16*(2), 91-112.

Johnson, K. (2018, February 28). Voice shopping may hit $40 billion by 2022 in the U.S. alone. *Venture Beat*. Retrieved from https://venturebeat.com/2018/02/28/voice-shopping-may-hit-40-billion-by-2022-in-the-u-s-alone/

Joo, J., & Sang, Y. (2013). Exploring Koreans' smartphone usage: An integrated model of the technology acceptance model and uses and gratifications theory. *Computers in Human Behavior*, *29*(6), 2512-2518.

Juniper Research. (2018, February 12). *Digital voice assistants in use to triple to 8 billion by 2023, driven by smart home devices* [Press release]. Retrieved from https://www.juniperresearch.com/press/press-releases/digital-voice-assistants-in-use-to-triple

Karahanna, E., & Straub, D. W. (1999). The psychological origins of perceived usefulness and ease-of-use. *Information & management*, *35*(4), 237-250.

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS quarterly*, 183-213.

Lunney, A., Cunningham, N. R., & Eastin, M. S. (2016). Wearable fitness technology: A structural investigation into acceptance and perceived fitness outcomes. *Computers in Human Behavior*, *65*, 114-120.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), 81-95.

Mathieson, K. (1991). Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior. *Information systems research*, *2*(3), 173-191.

Nasri, W., & Charfeddine, L. (2012). Factors affecting the adoption of Internet banking in Tunisia: An integration theory of acceptance model and theory of planned behavior. *The Journal of High Technology Management Research*, *23*(1), 1-14.

Ooi, K. B., & Tan, G. W. H. (2016). Mobile technology acceptance model: An investigation using mobile users to explore smartphone credit card. *Expert Systems with Applications*, *59*, 33-46.

Pai, F. Y., & Huang, K. I. (2011). Applying the technology acceptance model to the introduction of healthcare information systems. *Technological Forecasting and Social Change*, *78*(4), 650-660.

Park, E., & Kim, K. J. (2014). An integrated adoption model of mobile cloud services: exploration of key determinants and extension of technology acceptance model. *Telematics and Informatics*, *31*(3), 376-385.

Park, N., Lee, K. M., & Cheong, P. H. (2007). University instructors' acceptance of electronic courseware: An application of the technology acceptance model. *Journal of Computer-Mediated Communication*, *13*(1), 163-186.

Park, N. (2010). Adoption and use of computer-based voice over Internet protocol phone service: Toward an integrated model. *Journal of communication*, *60*(1), 40-72.

Park, S. Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning. *Educational technology & society*, *12*(3), 150-162.

PricewaterhouseCoopers. (2018). *Consumer intelligence series: prepare for the voice revolution.* Retrieved from PricewaterhouseCoopers (PwC) Website: https://www.pwc.com/us/en/advisory-services/publications/consumer-intelligence-series/pwc-voice-assistants.pdf

Ramos-de-Luna, I., Montoro-Ríos, F., & Liébana-Cabanillas, F. (2016). Determinants of the intention to use NFC technology as a payment system: an acceptance model approach. *Information Systems and e-Business Management*, *14*(2), 293-314.

Rauniar, R., Rawski, G., Yang, J., & Johnson, B. (2014). Technology acceptance model (TAM) and social media usage: an empirical study on Facebook. *Journal of Enterprise Information Management*, *27*(1), 6-30.

Reis, A., Paulino, D., Paredes, H., & Barroso, J. (2017, July). Using intelligent personal assistants to strengthen the elderlies' social bonds. In *International Conference on Universal Access in Human-Computer Interaction* (pp. 593-602). Springer, Cham.

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & management*, *44*(1), 90-103.

Stern, B. B., Royne, M. B., Stafford, T. F., & Bienstock, C. C. (2008). Consumer acceptance of online auctions: An extension and revision of the TAM. *Psychology & Marketing*, *25*(7), 619-636.

Suki, N. M. [Norazah Mohd], & Suki, N. M. [Norbayah Mohd] (2011). Exploring the relationship between perceived usefulness, perceived ease of use, perceived enjoyment, attitude and subscribers' intention towards using 3G mobile services. *Journal of Information Technology Management*, *22*(1), 1-7.

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information systems research*, *6*(2), 144-176.

Tractica. (2018, August 20). Artificial intelligence software market to reach $105.8 billion in annual worldwide revenue by 2025. *Tractica*. Retrieved from https://www.tractica.com/newsroom/press-releases/artificial-intelligence-software-market-to-reach-105-8-billion-in-annual-worldwide-revenue-by-2025/

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, *39*(2), 273-315.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204.

Wallace, T., & Morris, J. (2018, April). Identifying barriers to usability: smart speaker testing by military veterans with mild brain injury and PTSD. In *Cambridge*

Workshop on Universal Access and Assistive Technology (pp. 113-122). Springer, Cham.

Yang, H., & Lee, H. (2018). Understanding user behavior of virtual personal assistant devices. *Information Systems and e-Business Management*, 1-23.

Zhang, S., Zhao, J., & Tan, W. (2008). Extending TAM for online learning systems: An intrinsic motivation perspective. *Tsinghua Science and Technology*, *13*(3), 312-317.